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NONPOINT POLLUTION, WEEDS AND RISK

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Nonpoint pollution from agricultural production continues to force regulators to rethink policies aimed at reducing input sources such as herbicides and fertilisers. This paper considers how a producer's choice of an input strategy defined by application rate or persistence affects input-use patterns, and consequently, nonpoint pollution. Working within an endogenous risk framework, we explore how input sets with herbicides defined either as self-insurance or self-protection are affected by increased risk of herbicide treatment failure. Our results suggest that increased risk will generally decrease both herbicide and fertiliser application rates, resulting in the use of less flexible and less persistent herbicides. In addition, a quantity constraint policy restricting the amount of herbicide applied will decrease the amount of fertiliser applied.

1. Introduction

Agriculture is one of the largest contributors to nonpoint source pollution in the United States (USEPA, 1992). Griffin (1991) cites the United States Environmental Protection Agency's (EPA) national water quality inventory reporting that 50 to 70 per cent of "impaired or threatened surface water" is affected by nonpoint agricultural pollution. A substantial portion of agriculture's contribution to nonpoint pollution comes from crop production, with repeated detection of nutrient and pesticide sources in both surfacewater and groundwater (see Shortle and Dunn, 1986; Hanley, 1991; Russell and Shogren, 1993). Both human and ecosystem health are perceived to be threatened, thereby increasing the pressure to impose more regulation on input sources such as fertiliser and herbicides.

A common form of input source regulation is the quantity constraint, where a policy maker restricts or bans the use of certain inputs. The success of a quantity constraint, however, depends on the input substitution set faced by the producer. In agricultural production, this set includes both inter-input and

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intra-input substitution. Inter-input substitution captures the trade-off between the use of, say herbicides and fertiliser. Understanding how the producer trades off one for another given changes in his constraint system will reflect the degree of success of a policy. If a herbicide restriction induces more use of fertiliser, the policy maker has simply traded off one source of pollution for another (Crocker and Shogren, 1993). Intra-input substitution implies that the producer has a set of input strategies all aimed at one goal, say weed control, such that he can substitute one input strategy for another depending on how the quantity constraint alters relative prices. In the case of herbicides, the producer might consider trading quantity for persistence. The choice of an input strategy will also have an indirect effect on the use of other production inputs. Therefore, capturing the environmental effects of agriculture requires policy makers to consider how both the quantity and type of input affect the sources of nonpoint pollution. As an example, a regulation that limits the application rate of a herbicide has a direct and indirect effect. The direct effect is simply to reduce the amount of the herbicide applied. But even if the output mix is unchanged, the indirect effect acts to shift to other herbicides and change the amounts of fertilisers applied. These indirect effects impact both the level and intensity of nonpoint pollution, and consequently the effectiveness of the regulation.

This paper explores this relationship between nonpoint pollution, weed control and risk. We use an endogenous risk approach to model the relationship between both the types and quantities of herbicides used and the quantity of fertiliser used when a producer maximises expected profits. The endogenous risk approach captures a producer's view that a herbicide strategy can be used as either self-insurance or self-protection (Ehrlich and Becker, 1972; Beach and Carlson, 1993). Self-insurance and self-protection are investments to increase a producer's wealth or the probability that a good state of nature occurs – in our case, the control of weeds. We examine optimal input rates and persistence of herbicide given increased risk of herbicide treatment failure – application or effectiveness failure – and given a quantity constraint policy of restricted use levels. Application failure occurs if the producer fails to apply the herbicide, while effectiveness failure implies the applied herbicide fails to work, mainly due to weather conditions (e.g. too dry).

Our results suggest that increased risk of a herbicide treatment failure will generally decrease both herbicide and fertiliser application rates, and result in the use of less flexible and less persistent herbicides, tending to decrease nonpoint pollution. The results also show that a quantity constraint policy that restricts the amount of herbicide applied will tend to decrease the amount of fertiliser applied. Similarly, a policy that restricts the amount of fertiliser applied will tend to decrease the amount of herbicide applied. Finally, the results suggest that a policy restricting the use of more flexible and more persistent herbicides will decrease the amount of fertiliser applied, while a policy restricting fertiliser applications will induce the use of less flexible and persistent herbicides. Therefore, policies targeted at reducing nonpoint pollution from one input source can have the added impact of reducing the nonpoint pollution from another input source.

The paper proceeds as follows. Section 2 identifies important herbicide characteristics that determine both the source of nonpoint polllution and a producer's production decisions. Sections 3 and 4 present the endogenous risk models of herbicides as self-insurance and self-protection. Finally, our conclusions are offered in Section 5.

2. Herbicide Characteristics and Nonpoint Source Pollution

Most of economics' studies of weed control focus on either the optimal rate of herbicide application or the weed-density threshold for applying a herbicide. While this is relevant data to link production decisions to levels of nonpoint pollution, the transport of pesticides through the soil also depends on other pesticide characteristics such as aqueous solubility, saturated vapour pressure, and persistence (see Wagenet and Hutson, 1991). Using a statistical metamodelling approach, Bouzaher *et al.* (1993) estimated that the decay rate, Henry's law constant and soil sorption coefficient were significant predictors of the concentration levels of seventeen herbicides in surface and groundwater in the midwestern United States.* The question then is, are any of these other herbicide characteristics important in a producer's herbicide decision? We answer this question by considering the producer's decision about which herbicide to apply.

A producer considers many factors in deciding which herbicide to apply, including target weed species, timing of application, mode of application, and herbicide persistence. Of these factors, herbicide persistence is directly related to nonpoint pollution. Holden and Graham (1992) stress that the frequency of occurrence of herbicides in groundwater are due to both the likelihood of their use and their persistence in the soil. For example, atrazine is the most detected herbicide in surfacewater, groundwater and even in precipitation in the US corn belt (Goolsby *et al.,* 1991; Nations and Hallberg, 1992). Of the soil-applied herbicides used on corn, atrazine has the longest half-life; that is, the longest persistence (Becker *et al.,* 1989).

Herbicide persistence determines both a producer's flexibility to apply a herbicide and the probability that a herbicide application will be effective. In this way, the decision about which herbicide to apply determines the level of risk that a producer will face – the risk of weed control failure is endogenous. Granted the producer cannot alter the distribution of weather, but he can alter the probability and severity of a weed treatment failure through the selection of herbicide. Endogenous risk implies that a producer can affect the probability of losing yield to weeds by choosing a particular type of herbicide to apply, or that a producer can affect the magnitude of yield loss by choosing the amount of herbicide to apply (see Ehrlich and Becker, 1972; Hiebert, 1983; Shogren and Crocker, 1991).

Define self-protection as the decision about which herbicide to apply in terms of persistence, and self-insurance as the decision of how much herbicide to apply. By grouping herbicides into self-protection and self-insurance, we capture the intra-input substitution possibilities the producer can select. We also use the model to measure the relationship between herbicides as self-insurance or self-protection inputs and standard production inputs such as fertilisers. This allows us to examine the inter-input substitution trade-offs and the potential effect on nonpoint pollution.

3. Herbicides as Self-Insurance

Herbicides can only work if applied. In the US corn belt, weather conditions may prohibit a producer from applying a herbicide. For example, fields can be

* A metamodel summarises the input-output relationships in a simulation model. For example, in the case of pesticide leaching into groundwater, metamodelling simplifies the complex fate and transport system using statistically validated response functions. A metamodel reveals the key chemical and soil factors that influence herbicide concentrations in water, abstracting away from unnecessary detail, and thereby providing decision makers with timely information on alternative policy proposals. See Bouzaher *et al.* (1993) for further dicussion.

too wet for field work during the critical time when the herbicide must be applied to be effective. Recall we define this as "application failure". Once a herbicide is applied there is no guarantee it will be effective. Zimdahl (1980, ch. 6) describes critical periods during which herbicides must be effective in order to avoid significant yield losses. The time when these critical periods occur depends on weather conditions. If herbicide effectiveness runs out during a critical period or if there is a dry period after herbicide application, weeds may grow unchecked. Define this case as "effectiveness failure". For either type of failure yield losses can be substantial – Zimdahl (1980) cites studies of yield losses in corn near 38 per cent for high weed densities.

We model both application and effectiveness failures using a two state approach – a "good" state where there is no failure, and a "bad" state where a failure occurs. Assume the producer perceives the good state occurs with probability, g, and the bad state occurs with probability, $1-g$. Extending Pannell's (1990a) framework that captures the yield impacts of herbicide use, assume the producer has two decision variables – H is the amount of herbicide applied, and X is the amount of fertiliser applied. We include fertiliser to allow the producer the ability to influence full control yields. We reduce model complexity by assuming fertiliser can always be applied.

The producer's problem is to select X and H to maximise his expected profit, $E\pi$,

$$\text{Max } E\pi = g[PY_0(X)[1-D(W)] - rX - cH] + (1-g)[PY_0(X)[1-D(W_0)] - rX - \rho cH] \tag{1}$$

where damage, D(W), can occur in both states and is represented by the hyperbolic damage function suggested by Cousens (1985)

$$D(W) = a/[1 + a/(bW)] \tag{2}$$

W is weed density specified by

$$W = W_0 e^{-kH} \tag{3}$$

and W_0 is pre-treatment weed density. Let $Y_0(X)$ be the weed-free yield with $Y_0'(X)>0$ and $Y_0''(X)<0$, where primes denote relevant derivatives. Let P denote crop price, r the price of fertiliser, and c the price of the herbicide. The first term on the right hand-side of (1) represents the producer's profit if there is no failure; the second represents profit with failure. Let $\rho = 1$ represent the case of effectiveness failure where the producer incurs a herbicide cost in both states. Let $\rho = 0$ be the case of application failure where the producer incurs no herbicide cost. The producer incurs a fertiliser cost in both states since the fertiliser application occurs before a herbicide application failure is known.

Assuming an interior solution, the first order conditions for the producer's problem are

$$E\pi_X = PY'_0(X)[(1-g)(1-D(W_0)) + g(1-D(W))] - r = 0 \tag{4}$$

and

$$E\pi_H = -g[PY_0(X)D'(W)W'(H) + c] - (1-g)\rho c = 0 \tag{5}$$

Equation (4) implies the expected marginal value of fertiliser from both the good and the bad states equals the unit price of fertiliser. For effectiveness failure, equation (5) implies the expected marginal value of herbicide is equal to the unit price of herbicide. For application failure, equation (5) implies that the marginal value of herbicide in the good state is equal to the unit price of herbicide in the good state. The second order conditions require $E\pi_{XX}<0$, $E\pi_{HH}<0$, and $G \equiv E\pi_{XX}E\pi_{HH} - (E\pi_{XH})^2>0$, which are assumed to hold whenever the first order conditions are satisfied.

Let X^* and H^* represent the optimal levels of X and H. Consider the effect of an increase in the risk of a failure. We model the increase in the probability of failure as a decrease in the probability of the good state, g. The effects of a decrease in g on X^* and H^* are determined by

$$\frac{\partial X^*}{\partial g} = [-E\pi_{Xg}E\pi_{HH} + E\pi_{Hg}E\pi_{XH}]/\mathbf{G} \tag{6}$$

and

$$\frac{\partial H^*}{\partial g} = [-E\pi_{Hg}E\pi_{XX} + E\pi_{Xg}E\pi_{XH}]/\mathbf{G} \tag{7}$$

The first term in brackets on the right-hand-side of (6) represents the direct effect of a change in g on X^*, while the second term is the indirect effect on X^* through a change in H^*. Similarly, the first term in (7) is the direct effect of a change in g on H^*, and the second term is the indirect effect.

The sign of $E\pi_{XH}$ reveals whether the inputs are stochastic substitutes or stochastic complements. If **G** is the Hessian matrix of the problem and G_{ij} are the minors of **G**, Hiebert (1983) defines inputs i and j as stochastic substitutes (complements) if $G_{ij}<0$ (>0). We interpret stochastic substitutes to describe inputs where an increase in the optimal level of one input indirectly decreases the optimal level of the other input. Similarly, stochastic complements describes inputs where an increase in the optimal level of one input indirectly increases the optimal level of the other input.

Since damage due to weeds is higher without herbicide than with, then

$$E\pi_{Xg} = PY'_0(X)[D(W_0) - D(W)] > 0 \tag{8}$$

Using equation (5) we know

$$E\pi_{Hg} = -PY_0(X)D'(W)W' - (1-\rho)c \tag{9}$$

If $\rho=0$, $E\pi_{Hg}=0$; or if $\rho=1$, $E\pi_{Hg}>0$. Finally, assuming $D'(W)>0$ and $W'<0$

$$E\pi_{XH} = -gPY'_0(X)D'(W)W' > 0 \tag{10}$$

which implies that X and H are stochastic complements. Conditions (8)–(10) suggest that $\partial X^*/\partial g>0$ and $\partial H^*/\partial g>0$, which is summarised by the following proposition.

Proposition 1

An increase in the probability of effectiveness or application failure decreases the optimal application rates of both fertiliser and herbicide.

Note that an increase in the probability of application failure has no direct effect on the optimal level of herbicide – the effect derives from the stochastic complementary between fertiliser and herbicide. The only way application risk affects the optimal herbicide rate is by shifting the optimal fertiliser rate. This suggests that for some types of risk, changes in herbicide use depend only on changes in the use of fertiliser. This emphasises the importance of understanding that there are two effects of risk on optimal herbicide or fertiliser levels – a direct effect and an indirect effect. Even if risk does not have a direct effect on herbicide use, risk may produce changes in herbicide use indirectly through changes in optimal fertiliser rates.

A simple example illustrates. Suppose that a technological advance, such as a guidance system that allows herbicides to be applied more rapidly, decreases a producer's application risk. A policy maker who does not take into account the joint decision of fertiliser and herbicide rates will expect the technology to have no effect on herbicide application rates since the direct effect of application risk on the optimal herbicide rate is zero. However, in reality, the technology will increase optimal herbicide application rates indirectly through an increase in the optimal fertiliser application rate. By not taking into account the positive indirect effect of risk on herbicide use, the policy maker will underestimate the effect of the new technology on nonpoint source pollution from herbicides. The amount underestimated depends on the size of the indirect effect, indicating the importance of obtaining measures of substitution among inputs.

Whether the inputs are stochastic complements or stochastic substitutes also indicates the effect of a quantity constraint policy that restricts one input on the optimal level of the other input. Let there be a binding quantity constraint placed on the optimal herbicide application rate, $H^*=\hat{H}$. As an example from the US, herbicides legally must be applied at rates below maximum label rates. Recently, the maximum label rates for atrazine have been reduced from 3 pounds active ingredient applied per acre in a single year to 2.5 pounds active ingredient (Swoboda, 1993). The effect of the constraint policy on the optimal fertiliser application rate is

$$\frac{\partial X^*}{\partial \hat{H}} = -\frac{E\pi_{XH}}{E\pi_{XX}} \tag{11}$$

Using equation (10), this implies $\partial X^*/\partial \hat{H} > 0$. A policy restricting the herbicide application rate decreases the optimal fertiliser application rate. Similarly, the effect of a binding constraint placed on the optimal fertiliser application rate is

$$\frac{\partial H^*}{\partial \hat{X}} = -\frac{E\pi_{XH}}{E\pi_{HH}} \tag{12}$$

Again using (10), this implies $\partial H^*/\partial \hat{X} > 0$ – a policy restricting the fertiliser application rate decreases the optimal herbicide application rates.

Summarising the case of herbicides as self-insurance, an increase in either application risk or effectiveness risk decreases both the optimal herbicide rate and the optimal fertiliser rate. If this model holds, we expect to see lower herbicide application rates and fertiliser application rates used in areas of higher application and effectiveness risk. From a policy standpoint this implies that policies which shift production to farms with lower application or effectiveness risk will result in fertilisers and herbicides being applied at higher rates. It also implies that technologies which tend to decrease application or effectiveness risk will tend to increase fertiliser and herbicide application rates. In both cases we would expect to see an increase in the potential for nonpoint source pollution. Our results also indicate that a policy to reduce one source of nonpoint pollution may have the added effect of reducing another source of nonpoint pollution. A policy that restricts herbicide application rates can reduce fertiliser application rates, or vice versa.

4. Herbicides as Self Protection

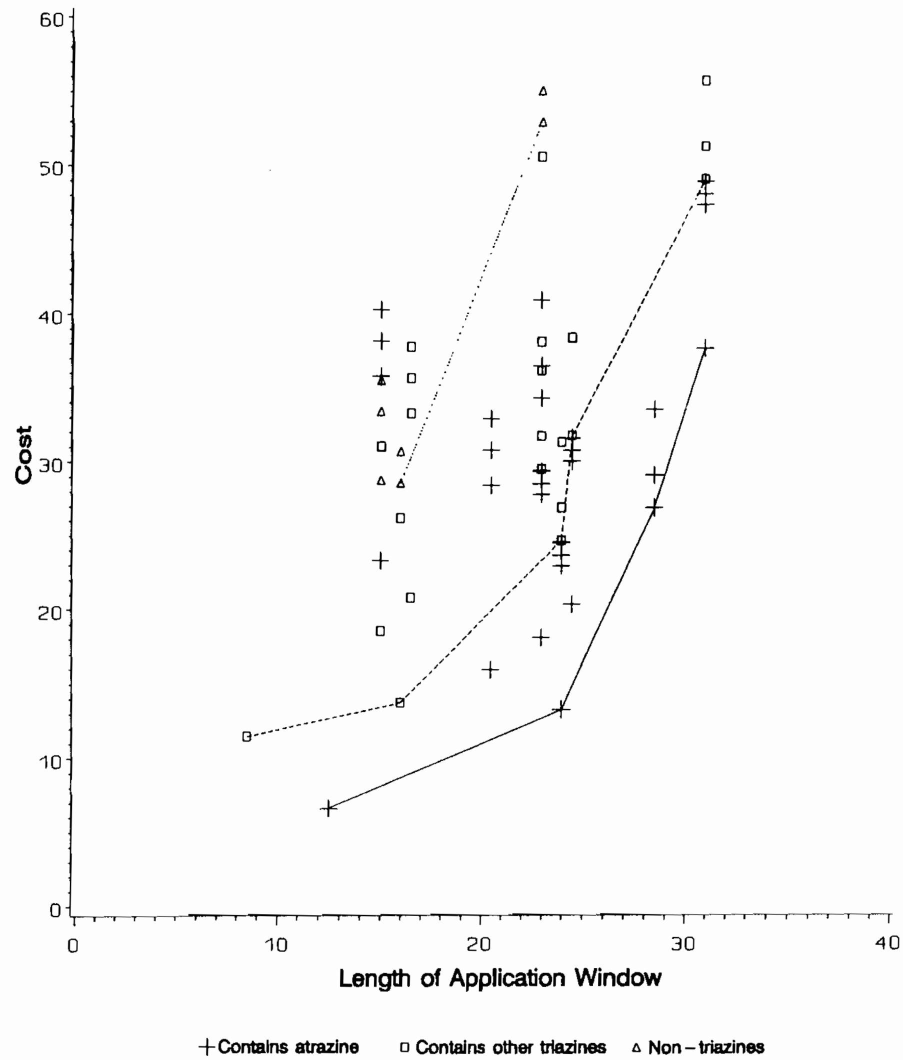
The preceding discussion considered the producer's weed control decision involving only the amount of herbicide to apply – self-insurance. Now consider the producer's choice of which herbicide to apply – self-protection. For application failure, the level of self-protection depends on herbicide characterisics that increase the probability of a successful application. If one herbicide can be applied over a longer time period than another then it will have a higher probability of being successfully applied. Bouzaher *et al.* (1992) quantify this time period for over 300 weed control strategies for corn, calling it the "application window". Similarly, for effectiveness failure, a herbicide that is effective over a longer period of time will have a higher probability of controlling weeds. Bouzaher *et al.* quantify this period as the "effectiveness window". An example illustrates. The critical period for pre-emergence application of Bladex to achieve full control in Iowa was estimated to be May 10 to May 25 – the length of the application window is 16 days. Bladex was also estimated to remain effective on broadleaf weeds for a period of 40 days after application and effective on grasses for 50 days. Without loss of generality, we simplify the analysis by focusing on only one application window.

Let q denote the length of the relevant window. Assume that for the available herbicides, self-protection, q, is a continuous variable.* The length of the effectiveness window determines the probability a herbicide is effective once applied, while the length of the application window determines the probability a farmer is able to apply the herbicide. The probability of the good state, g, is redefined as $g(q)$, with $g'(q)>0$. The unit cost of the herbicide will also depend on q, such that c is redefined as $c(q)$. Presumably herbicides that provide longer effectiveness or application windows are more expensive, implying $c'(q)>0$. If this were not the case, we would expect a corner solution with q either at zero or at a technological maximum.

Consider the weed control strategies defined by Bouzaher *et al.* (1992). Figures 1 and 2 show the application and effectiveness window lengths and the cost of each strategy applied on reduced tillage and a clay soil. In each figure, the solid line joins strategies which provide the longest combined window lengths for a given cost and is indicative of the cost function a producer faces. As window lengths increase, costs also increase at an increasing rate. Figures 1 and 2 also illustrate the effect of banning the use of various herbicides. The dashed line joins strategies that provide the longest combined window lengths for a given cost, after eliminating the strategies containing atrazine. Banning atrazine shifts the cost curve upward and to the left, so producers must pay a

* Choosing a herbicide is a discrete choice implying the choice of window length is also discrete. To maintain mathematical tractability, we assume the discrete nature of the problem can be approximated by a continous variable.

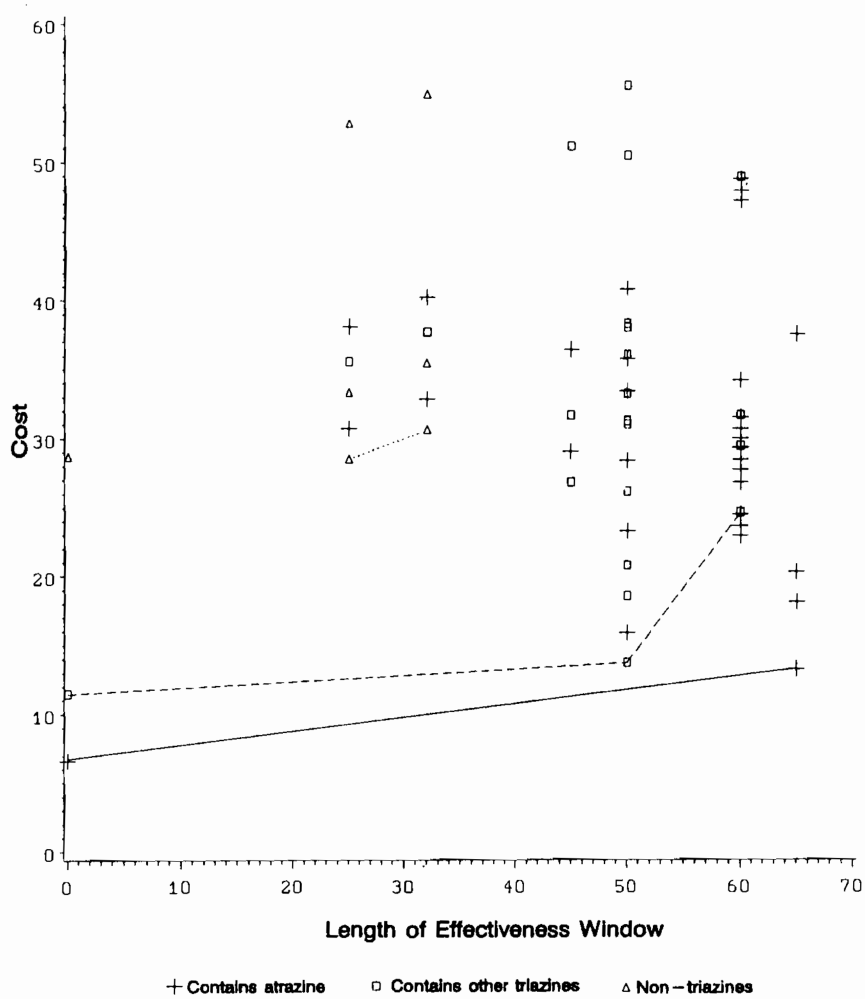
Figure 1 Efficient Application Window



higher price to purchase herbicides with equal window lengths. Also, herbicides with the longest window lengths are eliminated. Similarly, the dotted line joins strategies that provide the longest combined window lengths for a given cost eliminating all strategies that contain triazines. Banning triazines further shifts the cost curve upward and to the left, again increasing the price a producer pays for a given window length and restricting the choices to smaller window lengths.

Assume the farmer takes herbicide application rates as fixed – the farmer applies a herbicide only at the recommended rate. In the self-protection model, the producer chooses the optimal effectiveness or application window and the

Figure 2 Efficient Effectiveness Window



optimal fertiliser rate. The profit maximising producer's problem is now

$$\begin{aligned} \text{Max } E\pi &= g(q)[PY_0(X)[1-D(W)] - rX - c(q)H] \\ &+ (1-g(q))[PY_0(X)[1-D(W_0)] - rX - \rho c(q)H] \end{aligned} \tag{13}$$

This problem corresponds to the self-protection problem used by Hiebert, with q representing the self-protection good. The key difference is that for application uncertainty (i.e. $\rho=0$) the cost of self-protection appears only in the good state. The first order conditions for the problem are

$$E\pi_X = PY'_0(X)[(1-g(q))(1-D(W_0)) + g(q)(1-D(W))] - r = 0 \tag{14}$$

and

$$E\pi_q = g'(q)PY_0(X)[D(W_0) - D(W)] - (1-\rho)H\{g'(q)c(q) - g(q)c'(q)\} - \rho c'(q)H = 0 \tag{15}$$

As in the self-insurance case, (14) implies the expected marginal value of fertiliser over both the good and bad states is equal to the unit price of fertiliser. For effectiveness risk, equation (15) requires that the marginal benefit of q in shifting the probability toward the good state is equal to the marginal cost of q. For application risk, the net marginal benefit of q is equal to the expected marginal cost of q. The second order conditions require $E\pi_{XX}<0$, $E\pi_{qq}<0$, and $J \equiv E\pi_{XX}E\pi_{qq} - (E\pi_{Xq})^2>0$.

Now consider how self-protection is affected by an increase in the risk of failure. Following Hiebert, suppose g(q) has the form $g(q) = \alpha + \beta h(q)$, with $h'(q)>0$ and $\beta>0$. Increased risk occurs by decreasing either α or β. A decrease in α represents a constant increase in the probability of a failure for all lengths of the effectiveness or application window, q. Think of decreasing α as increasing the probability of failure independent of the length of the application window. A decrease in β represents an increase in the probability of a failure (increasing along q) through a decrease in the productivity of q. A decrease in β is described by site specific effectiveness or application technology. If two identical producers apply herbicides on two different soil types, but the herbicide breaks down more slowly on the first farmer's soil than on the second, the effectiveness window is more productive for the first farmer. Alternatively, if two producers apply herbicides to equal areas of land and one producer applies more rapidly than the other, the producer who takes more time has a lower application window productivity. Climate is another way to think of a decrease in β. Comparing a farm in the southern corn belt to one in the North, if the southern farm tends to have more days suitable for field work than the northern farm, the northern farm must make less use of a given application window. Fewer days suitable for field work corresponds to a lower β.

The effects of a decrease in α on X^* and q^* are determined by

$$\frac{\partial X^*}{\partial \alpha} = [-E\pi_{X\alpha}E\pi_{qq} + E\pi_{q\alpha}E\pi_{Xq}]/J \tag{16}$$

and

$$\frac{\partial q^*}{\partial \alpha} = [-E\pi_{q\alpha}E\pi_{XX} + E\pi_{X\alpha}E\pi_{Xq}]/J \tag{17}$$

Assuming second order conditions hold implies $E\pi_{XX}<0$, $E\pi_q<0$, and $J>0$. Given damage is higher without herbicide than with, we know

$$E\pi_{X\alpha} = PY'_0(X)[D(W_0) - D(W)] > 0 \tag{18}$$

and given $g'(q) > 0$

$$E\pi_{qX} = -g'(q)PY'_0(X)[D(W_0) - D(W)] > 0 \tag{19}$$

Given $c'(q) > 0$, then we know

$$E\pi_{q\alpha} = -(1-\rho)c'(q)H \tag{20}$$

If $\rho=1$, $E\pi_{q\alpha}=0$; or if $\rho=0$, $E\pi_{q\alpha}<0$. Equation (18) implies the direct effect of a decrease in α on X^* decreases the optimal level of fertiliser use. By definition, equation (19) implies q and X are stochastic complements. For effectiveness risk, equation (20) implies there is no direct effect of a decrease in α on q^*. For application risk, equation (20) implies the direct effect of a decrease in α on q^* increases the length of the optimal application window. If $\rho=1$, we have $\partial X^*/\partial \alpha>0$ and $\partial q^*/\partial\alpha>0$.

Proposition 2

Holding herbicide application rate and the effectiveness of self-protection constant, an increase in the probability of effectiveness failure decreases both the optimal fertiliser rate and the optimal length of the effectiveness window.

It is likely that herbicides with shorter effectiveness windows tend to decay more rapidly in the environment. This indicates that an increase in effectiveness risk that leaves the productivity of the effectiveness window unchanged may reduce potential negative environmental impacts of agricultural chemicals both by reducing the amount of fertiliser applied and by reducing the persistence of herbicides that are used. It is important to note, however, that herbicide application rates are held constant. Reconsidering Figures 1 and 2, we note that as window lengths increase we move out of the strictly non-triazine activities, and as window lengths continue to increase we move into activities which all contain atrazine.

For application risk, given the signs of the direct effects, knowing that q and X are stochastic complements shows that the direct and indirect effects of increased risk work in opposite directions for both X^* and q^*. This implies that the signs of $\partial X^*/\partial\alpha$ and $\partial q^*/\partial\alpha$ are ambiguous. In contrast to self-insurance, herbicide use as self-protection does not necessarily imply that increased risk decreases optimal input levels. The ambiguity emanates from a decrease in the expected marginal herbicide cost due to an increase in the probability that the herbicide cannot be applied. This increases the optimal length of the application window. Since the length of the application window and the fertiliser rate are stochastic complements, this increases the optimal fertiliser rate. However, the marginal value of fertiliser is reduced by an increase in the probability of failure which decreases the optimal fertiliser rate. Since the length of the application window and the fertiliser rate are stochastic complements, this also decreases the optimal fertiliser rate. If the decrease in expected marginal cost of q is offset by the decrease of expected marginal revenues due to the increased probability of failure, then self-protection would increase. Note that for effectiveness risk, there is no decrease in expected herbicide cost due to increased risk, thereby eliminating any ambiguity.

The effects of a decrease in the productivity of self protection, β, on X^* and q^* are determined by

$$\frac{\partial X^*}{\partial\beta} = [-E\pi_{X\beta}E\pi_{qq} + E\pi_{q\beta}E\pi_{Xq}]/J \tag{21}$$

and

$$\frac{\partial q^*}{\partial \beta} = [-E\pi_{q\beta}E\pi_{XX}+E\pi_{X\beta}E\pi_{Xq}]/J \tag{22}$$

Given the second order conditions hold and equation (19), $E\pi_{XX}<0$, $E\pi_{qq}<0$, and $J>0$, and $E\pi_{qX}>0$. Again since damage without herbicide is greater than damage with herbicide

$$E\pi_{X\beta} = h(q)PY'_0(X)[D(W_0)-D(W)] > 0 \tag{23}$$

Using the first order condition (15), $E\pi_q=0$

$$E\pi_{q\beta} = ((1-\rho)\alpha c'(q)H)/\beta + \rho(h'(q)PY_0(X)[D(W_0)-D(W)]) > 0 \tag{24}$$

The signs of (23) and (24) allow us to determine that $\partial X^*/\partial\beta>0$ and $\partial q^*/\partial\beta>0$, which is summarised below.

Proposition 3

Holding herbicide application rates constant, an increase in the risk of effectiveness or application failure through a reduction in the productivity of self-protection decreases both the optimal fertiliser application rate and the optimal length of the effectiveness of application window.

For effectiveness risk, this is the same result as a shift in g(q) leaving the productivity of q unchanged. Assuming herbicide application rates are held constant, increased risk through a decrease in the productivity of the effectiveness window will have positive environmental impacts since fertilisers are used at lower rates and the herbicides used will tend to decay more rapidly. For application risk, proposition 3 differs from the shift in g(q) because the direct effects of decreasing α versus decreasing β have opposite effect on q^*. The direct effect of decreasing α increases the optimal application window, while the direct effect of decreasing β decreases the optimal application window. This difference occurs because a decrease in α decreases the expected marginal cost of q but leaves the marginal benefit of q unchanged, implying it is more attractive to apply a herbicide with a longer application window. However, for a decrease in β, in order for the first order conditions to hold, the marginal benefit of q decreases more rapidly than the expected marginal cost implying it is less attractive to apply a herbicide with a longer application window.

Again consider Figures 1 and 2. An increase in risk through a decrease in the productivity of the application window results in a shift from non-triazine activities to activities containing triazines. If we think of herbicides with longer application windows as being more potent, a shift toward longer application windows may be associated with more damaging sources of nonpoint source pollution. In this case an increase in risk through a decrease in the productivity of the application window decreases the potential damage associated with nonpoint source pollution. However, if the productivity of self-protection, q, endures given increased risk, this might not hold. Understanding the source of application risk is useful in determining its impact on the environment.

Looking at equation (19) we note that q and X are stochastic complements. Similar to the self-insurance problem, this implies that a policy that restricts the use of herbicides with longer effectiveness or application windows will decrease fertiliser application rates. In addition, a policy that restricts fertiliser application rates will tend to decrease the use of more flexible herbicides.

Summarising the herbicide as self-protection case, an increase in effectiveness risk decreases both the optimal fertiliser rate and the length of the optimal application window. If this model holds, we expect to see lower fertiliser application rates and less persistent herbicides being used in areas of higher effectiveness risk. From a policy standpoint, this implies that policies which shift production to farms with higher effectiveness risk will increase fertiliser application rates and lead to use of more persistent herbicides. For an increase in application risk, the result is not so clear. An increase in application rates through a decrease in the productivity of the application window decreases both the optimal fertiliser rate and the length of the optimal application window. In this case we expect to see lower fertiliser application rates and less potent herbicides used in areas of higher application risk. If the increase in application risk leaves the productivity of the application window unchanged, however, the effect on the optimal fertiliser rate and the length of the optimal application window is ambiguous. Our results also show that a policy designed to restrict fertiliser application rates can lead to use of less flexible, and presumably less persistent herbicides. Similarly, a policy designed to restrict the use of more flexible herbicides will reduce fertiliser application rates. Consequently, policies that have the direct effect of reducing one source of nonpoint pollution may have a positive indirect effect of reducing another.

5. Conclusion

We use an endogenous risk model to explore the effects of weed treatment risk and nonpoint pollution policy on the types of herbicides used as well as their quantities. This framework also allows us to understand inter-input substitution between herbicides and fertilisers. In most cases, our results suggest that risk tends to decrease the quantities of herbicides and fertilisers used and leads to use of less persistent herbicides. This would indicate risk of weed control failure has an unambiguous effect on nonpoint pollution from these sources. Consequently as risk reducing technologies become available we should expect nonpoint pollution problems to increase.

Our results suggest that herbicide quantities and fertiliser quantities are stochastic complements, so policies that restrict one of these quantities may have the indirect effect of decreasing the other. This would increase the effectiveness of a policy aimed at decreasing nonpoint pollution. Similarly, our results indicate that herbicide persistence and fertiliser quantities are stochastic complements, implying that policies that restrict one of these will have the indirect effect of decreasing the other. Again this would increase the effectiveness of nonpoint pollution policy.

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